

# IoT based FRAN Architecture using Cloud and Edge Detection System

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**Abstract:** A multi-cell Fog-Radio Access Network (FRAN) architecture that takes into consideration the noisy interference from Internet of Things (IoT) devices and transmission takes place in the uplink with grant-free access. An edge node is used to connect the devices present in every cell and will hold a reasonable capacity in the central processor. The readings obtained from the IoT devices are used to determine the field of correlated Quality of Interests in every cell, transmitting using the Type-Based Multiple Access (TBMA) protocol. This is in contrast to the conventional protocols that are used for diagnostic purpose. In this proposed work, we have implemented the multi-cell FRAN using cloud or edge detection in analysing the form of information-centric radio access. In a multi-cell system, cloud and edge detection are implemented and analysed. We have implemented model-based detectors and the probability of error for the asymptotic behavior in edge as well as cloud is determined. Similarly, cloud and edge detectors that are data driven are used when statistical models are not available.

**Keywords:** 5G, Information-centric access, Fog-RAN, IoT, Type-Based Multiple Access, Grant-Free Access

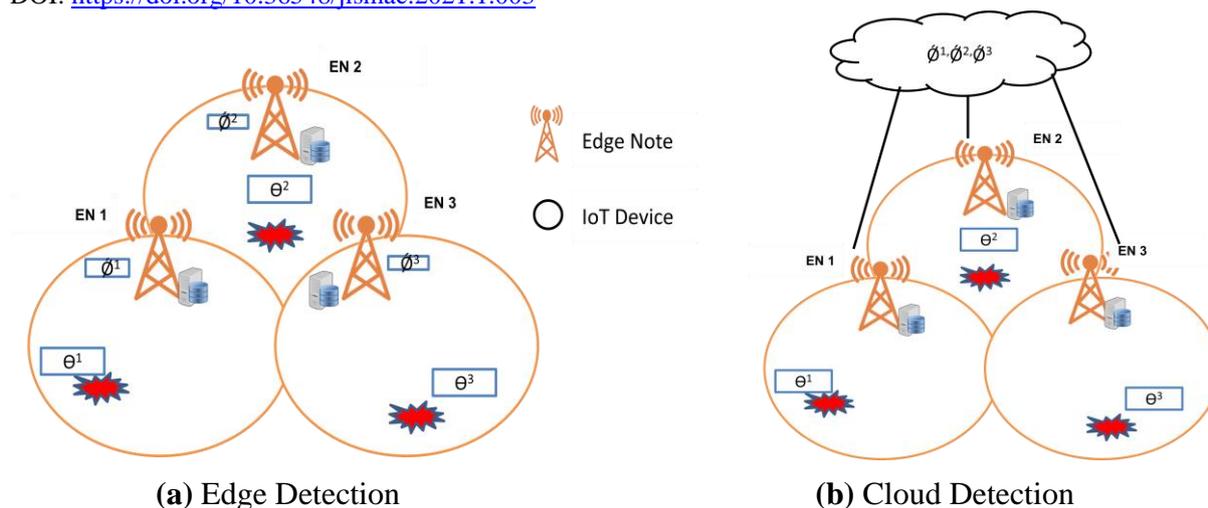
## 1. Introduction

The currently existing IoT systems are implemented using proprietary protocols like Sigfox and LoRa and are used in low-duty cycle, long-range transmission. The introduction of Narrow Band IoT along with the growth of 5G has played a major role in boosting IoT's development and usage. The IoT based cellular systems are known for their coverage and

reliability. However, they also face multiple challenges in terms of system optimization and interference management. A common primitive communication used is grant free access. Here, randomly selected preambles are used to for transmission purpose by the devices. Since the packets are usually built with the same configuration as that of an independent message, the information that is sent is generally random access. In this work, we have identified that an IoT system will hold preambles that can be repurposed in a TBMA protocol to act as building blocks for remote estimation. Hence, we have introduced a novel TBMA that incorporates information- centric protocol that can be used to determine a grant-free access scheme that is extremely efficient. Fig.1 shows an illustration of the problem at hand. Consider an IoT app that can be used to determine the field and spatial distribution. A good example is the use of IoT to determine the level of pollution in particular geographical vicinity. IoT devices are used as sensors that are used to correlate information with the help of QoI determined from the locations nearby. A typical approach that is used is the Sigfox that is used for transmitting the results to the local edge node with the help of grant-free access. Hence the solution will have many drawbacks that will be addressed like the following:

- The EN is detected locally and will not leverage the existing cloud or central processor to use the fronthaul links to multiple EN.
- The communication protocol will not be suitable for correlating the observations made by the devices in order to obtain the observations individually.

The 3GPP documents will hold the Central Units or cloud processors which cellular architectures are used as Fog-Radio Access Network (FRAN) [1]. A typical TBMA [2] is based on the fact that the parameter-dependent measurements in a histogram will suffice to optimally analyze a particular parameter while the individual observations are not required. Hence, traditional schemes of transmission that make use of separate observations at the receiving end will prove to be ineffective. On the other hand, the TBMA is developed such that based on the observations made, a histogram is estimated. Using appropriate quantization, all the devices are used in TBMA to measure and transmit the same wave. In this proposed work, we have incorporated a FRAN using TBMA-based methodology where cloud or edge detection [3] is used for inter-cell non-orthogonal frequency integration with TBMA.



**Fig.1.** (a) Edge Detection and (b) Cloud Detection

## 2. Related Works

Based on the different deployments of IoT systems and the different scenarios, they are studied from various viewpoints in this session. Studies have been conducted on unsourced random access with information theoretical analysis in areas of machine learning and neural network. Any correlation in the messages of the device is disregarded in the conventional methods. Moreover, correlation of the messages using a simple correlation model will be used with a simpler message as an alarm. The issue which involves location observations, leading to distributed detection uses the analogy of transmission taking place in an orthogonal manner and extensive study on the same has been made by many researchers [4]-[6]. A good example is that of problem detection in a distributed environment in the presence of multiple antennas located at the receiver. Using non-orthogonal input, the TBMA can execute NOMA access which is used to transmit information in IoT devices. Unlike the traditional NOMA used, based on the data that is to be transmitted, the communication protocol is altered. Hence, it can be considered as a joint source-channel coding that requires more concentration on power efficiency and potential spectrum in the IoT systems. In a related work published recently [7], a novel message transmitting technique by means of TBMA in non-orthogonal network with source channel coding is proposed. Similarly, a hybrid non-orthogonal and orthogonal MAC [9] using TBMA is also incorporated [8]. The

issue of performance tradeoffs between processing at cloud and edge is diagnosed in this work inclusive of coexisting 5G services, scheduling and content delivery.

### 3. Proposed Work

A system model is represented in the Fig.1 where the proposed FRAN Fog network is used to identify the QoI fields [10] like pollution level and temperature level, according to signal that is received via the IoT system. Every cell that is present comprises of many IoT devices and a single-antenna Edge Node. Let us consider that a random variable is used to describe the QoI such that it represents the cell correlation with respect to every device within the cell. Let us consider  $\theta^p$  to indicate the pollution level of the cell 'p' such that it can take the values  $\theta_1$  or  $\theta_0$ . Setting correlation intervals at 'L', the local EN [11-12] will interrogate the IoT devices in a periodical fashion. In every interval, the measurements made are transmitted from every cell 'c' using the grant-free access protocol in the uplink. Discontinuous access to energy communication devices as well as QoI can be modelled using the random activation pattern. In a particular interval range of  $R=1,2,\dots,L$ , every device in that particular area is going to be active such that it acts as an independent device with respect to the sensor. Hence the probabilistic mass function can be represented as:

$$\Pr[N_R^c = n] = P(n|\lambda)$$

where  $\lambda$  represents mean, and  $N_R^c$  denotes the number of active devices within the given interval R. Since the transmission of information takes place within the same spectrum, the devices will share the spectrum using the devices across various cells or inside the same cell. Cloud and Edge detection are the two architectures that can be used for QoI detection. Every EN will initially quantize the signal received and then forward it to the cloud processor. The purpose of this process is to determine the estimates of the QoI ( $\theta^p$ ). In a particular cell, c, the active IoT device is measured in terms of  $X_{i,R}^c$  such that for a given size S, it takes up the values in the range  $\{1,2,3,\dots,S\}$ . If the obtained values are in the analog form, it can be further quantized into S levels. In this paper, we have used mean-squared error during the process of quantization such that  $\frac{\Delta^2}{12}$  is the mean squared error and size of the step is denoted as  $\Delta$ . Based on QoI, the distribution is observed such that:

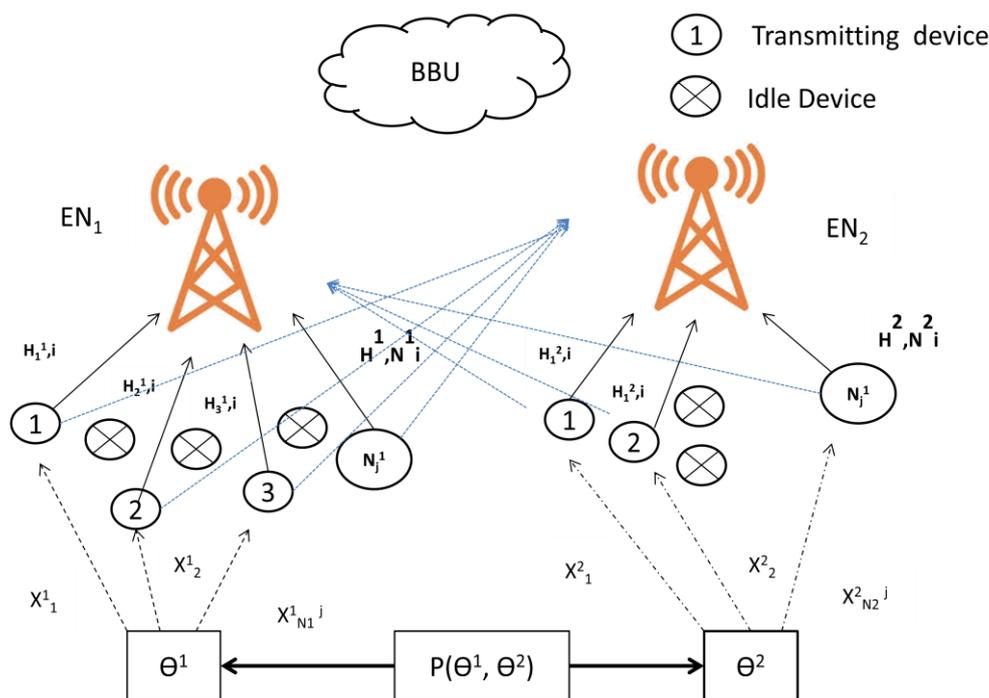
$$\Pr[X_{i,R}^c = m | \theta^c = \theta_0] = p_0^c(m) \quad (1)$$

$$\Pr[X_{i,R}^c = m | \theta^c = \theta_1] = p_0^c(m) \quad (2)$$

where  $m=1,2,3,\dots,M$ . Fig.2 shows a case with two cells that is used to determine the actual problem without distorting the function. Joint distribution of QoI in this proposed work based on the correlation between the two cells in terms of QoI can be expressed as follows:

$$p(\theta^1, \theta^2) = \frac{\rho}{2} 1_{\{\theta^1=\theta^2\}} + \frac{1-\rho}{2} 1_{\{\theta^1 \neq \theta^2\}}$$

Here  $\rho$  denotes the ‘correlation parameter’ which has a value between 0 and 1 indicating the probability of the two QoIs.



**Fig.2.** Interference in a Two-System Model

In this methodology, the TBMA-based protocol revolves round the information gathered and uses that to determine a correlation between the different cells and different devices. Let us consider M orthogonal waveforms within the bandwidth allotted and the time period for every collection interval. In general, the random access phases will hold preambles that will serve as waveforms of cellular standards. The information observed is transmitted in the uplink by means of these waveforms in the IoT devices. When used in non-orthogonal frequency, the signal transmitted can be represented as:

$$S_{i,R}^c(t) = \sqrt{E_s} \phi x_{i,R}^c(t)$$

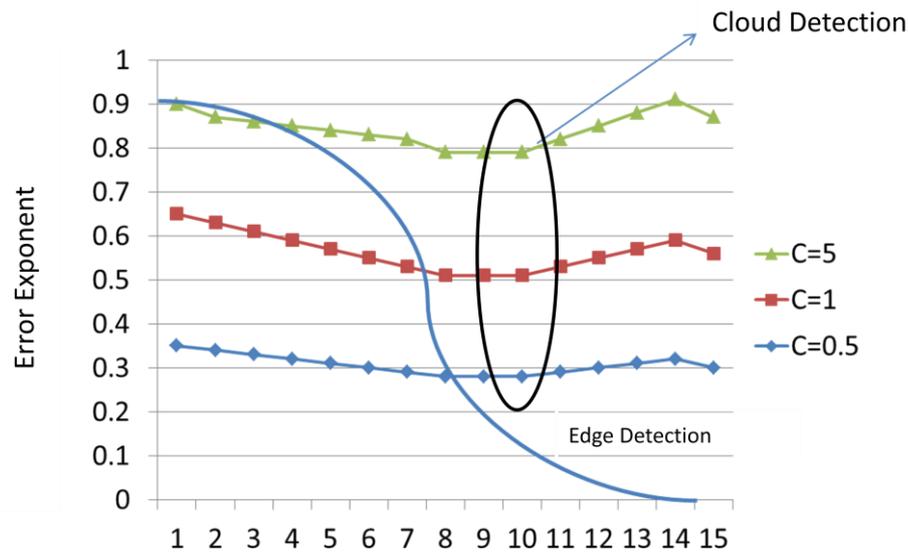
where the interval is denoted as R and the cell is represented as c. Using joint error probability, the performance of both edge as well as cloud detection can be evaluated such:

$$P_e = \Pr [\hat{\theta}^c \neq \theta^c]$$

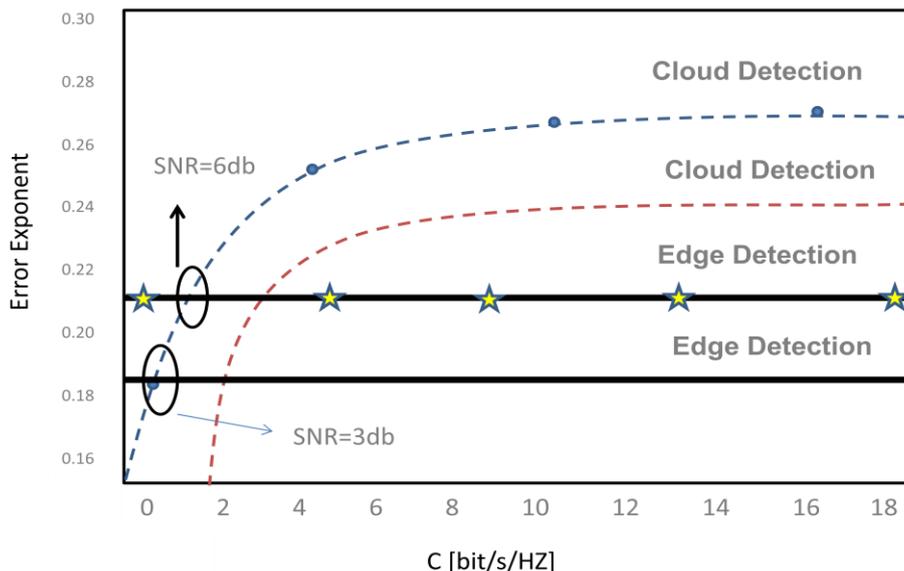
where  $\hat{\theta}^c$ , shows an estimate of QoI that is observed from the FRAN architecture.

#### 4. Results and Discussion

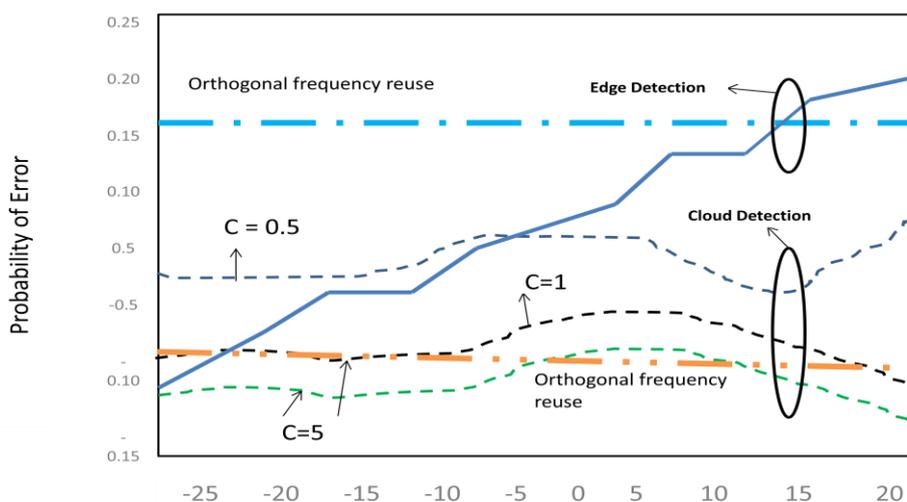
Here the multi-antenna receiver is used in the overall cloud-based system and the gain observed in decoding takes placed based on the reception. Fig.3 shows the gain obtained when modifying the cloud decoded output amidst limited fronthaul capacity. When this is small, it is observed that the cloud performs better than that of edge detection. However when both the cloud as well as edge detection have the same performance the detection of the former will outweigh the latter when the value of  $\sigma$  is higher.



**Fig.3.** Error Exponent for ‘inter-cell power gain’



**Fig.4** Error exponent for varying ‘C’



**Fig.5** Error Probability for Cloud and Edge Detection

Fig.4 shows the impact of fronthaul capacity ‘C’ in identifying the relative performance of the edge and cloud detection where the error exponent is plotted as function of ‘C’. From the figure it is seen that as the value of C increases, a subsequent increase in the value of cloud’s detection is also observed. Similarly, Fig.5 shows that the error probability with respect to inter-cell power gain is higher for edge detection when compared to that of cloud detection.

## 5. Conclusion

The proposed work addresses the problem in a FRAN architecture with respect to the detection of QoI. Here a TBMA algorithm is combined with an grant-free access scheme which is information-centric. Here, the QoI identified with the proposed architecture is found to perform better when compared to that of edge detection based architecture which is affected by inter-cell power gains that exceeds the predefined limits. This could also be verified analytically with the help of measurements gathered from asymptotic regime. The proposed work is carried out with the help of random access preambles that are used in typical protocols of a cellular network. The TBMA proposed will change only the preambles interpretation without any impact on the IoT devices' physical existing layers.

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